Asian Economic and Financial Review
ISSN(e): 2222-6737
ISSN(p): 2305-2147
DOI: 10.55493/5002.v15i1.5257
Vol. 15, No. 1, 1-26.

URL: www.aessweb.com

Evaluating diversification approaches: A comparative analysis of traditional, Islamic indices in the United Kingdom, and alternative investment options

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Article History
Received: 14 May 2024
Revised: 29 October 2024
Accepted: 21 November 2024
Published: 1 January 2025

Keywords
Bitcoin
Crude oil
Gold
MODWT
Portfolio diversification benefits
United Kingdom
Wavelet.

JEL Classification:
C22; C58; E44; G15.

ABSTRACT

This study explores the diversification potential of the United Kingdom's (UK) conventional and Islamic stock indices, Bitcoin, gold, crude oil, and the GBP/USD exchange rate from 2011 to 2022 using methodologies such as VECM, MODWT, MGARCH-DCC, and CWT. The findings indicate that UK indices, gold, and Bitcoin respond to changes in crude oil prices and GBP/USD rates, whereas GBP/USD and crude oil show low correlation, offering diversification benefits. Gold consistently maintains a low correlation with UK indices during global disruptions, such as the 2020 pandemic and the 2022 Ukraine-Russia conflict, reinforcing its reliability as a diversification asset. However, Bitcoin shows potential as a diversification tool despite its high volatility, which is a concern. Crude oil's effectiveness as a diversification asset diminishes for holding periods beyond 64 trading days. The study also reveals that the global financial crisis significantly impacted both UK Islamic and conventional indices, challenging the role of the Islamic index as a safe haven and suggesting that Shariah screening may not necessarily shield Islamic markets during economic downturns. These findings provide investors with essential insights into selecting equity indices and commodities for portfolio diversification and underscore the importance of advanced methodologies to understand correlation and volatility dynamics.

Contribution/ Originality: The originality of this study lies in its integration of Bitcoin alongside conventional and Islamic stock indices, gold, crude oil, and GBP/USD exchange rates using advanced methodologies like MODWT, MGARCH-DCC, and CWT, providing new insights into Bitcoin's diversification potential and comparing Islamic and conventional indices during global crises.

1. INTRODUCTION

Investors need to diversify their portfolios to reduce risk, aiming to construct investment portfolios backed by diversification planning to minimise the risk associated with their investment assets while growing those portfolios at a reasonable rate. Typically, investors construct investment portfolios with negatively or lowly correlated stocks. However, searching for stocks with low correlation becomes more challenging over time due to economic events that similarly affect most companies and industries. This process has led to the financialisation of the stock markets, where huge funds from various investors, such as hedge funds, mutual funds, pension funds, and financial institutions, have invested aggressively in companies from different industries to reduce their risk. Due to the high correlation, this strategy has resulted in fewer opportunities to diversify stocks across different industries. To resolve this, investors have started paying more attention to different markets to manage risk.

Commodities are among the preferred investments to reduce portfolio risk. Commodities behave differently from stocks and bonds because their prices are not sensitive to discount rate changes. According to Anson (2002) commodity prices are subject to demand and supply and are not valued using the discounted cash flow method. Historically, people have traded commodities, but due to lack of liquidity, physical delivery, and counterparty risk, there were restrictions on commodity investment. Since the establishment of the commodity exchange in 1848 with the Chicago Board of Trade (CBOT), commodities market investment has flourished. Many other commodities exchanges were subsequently established, leading to the transfer of liquidity, physical delivery, and counterparty risk to the clearinghouses. Investors began investing in the commodities exchanges to gain from speculative trading and diversify their portfolios. However, excessive investment from investors (mutual funds, financial institutions, and pension funds) has reduced the diversification advantages in the commodities markets due to the increasing correlation of the commodities markets with the stock market (Plantier, 2013).

The quest for alternative investment instruments has continued with the emergence of Bitcoin. Bitcoin's substantial daily returns and trading volume have attracted investors. For example, an investment of USD1,000 in Bitcoin in July 2010, when it was priced at USD0.08 per coin, would have resulted in a return of USD247 million by December 2017, when the price soared to USD19,783 per coin. This significant return also comes with high volatility, as Narayan, Narayan, Rahman, and Setiawan (2019) noted. Consequently, this article analyses Bitcoin to better understand the associated risks. As of February 2023, Bitcoin is valued at approximately USD25,000 per coin, with a market capitalisation of around USD485 billion. Bitcoin has become a major cryptocurrency, with numerous prominent financial institutions investing heavily in it and various merchants accepting it as a payment method like other currencies. According to Gajardo, Kristjanpoller, and Minutolo (2018) cryptocurrency can reduce transaction costs, offer robust security for online transactions, and potentially mitigate exchange rate risks. Despite Bitcoin's rise to mainstream acceptance, its behaviour has not been thoroughly examined. This has led us to include Bitcoin as a variable for further investigation. We aim to study Bitcoin's price movements with UK stock indices and other commodities, such as oil and gold, to assess potential diversification benefits. Although interest in Bitcoin for online trading is growing, there is limited empirical evidence regarding its hedging capabilities, diversification advantages, and safe haven properties compared to other commodities and stock indices. This study seeks to address this gap by exploring Bitcoin's role in portfolio diversification and risk management alongside traditional financial assets.

Numerous stock market indices experienced a substantial decline from late February to late March 2020 due to the COVID-19 pandemic, followed by intermittent volatility and a gradual recovery (Zhong & Wu, 2020). In today's increasingly interconnected global economy, addressing the rapid spread of financial risks following major global crises has become a critical concern for policymakers and academics. This article investigates whether the COVID-19 pandemic and the Russia-Ukraine conflict have triggered volatility in the UK Islamic and conventional indices and explores the impact of these events on the risk correlation between commodities and UK indices. We focus on UK indices because the UK hosts the London Stock Exchange (LSE), one of the world's largest stock exchanges by market capitalisation. The findings of this paper may help academics and policymakers gain a deeper understanding of the risk correlations and volatility between commodities and UK stock indices.

This study addresses several key research questions: First, what is the dynamic causal relationship between the UK's Conventional Stock Index Return (CSIR) and Islamic Stock Index Return (ISIR) in relation to commodities such as gold, crude oil, and Bitcoin prices? Second, to what extent can the historical values of stock indices predict the price movements of these commodities? Third, which exogenous variables exhibit greater exogeneity across different time horizons? Fourth, what key variables should investors focus on to maximise portfolio diversification benefits? Finally, How do the benefits of portfolio diversification vary across different investment horizons and stock-holding periods?

This study uses advanced methodologies to examine the potential for portfolio diversification across different investment horizons. The findings from this research aim to help a diverse group of investors optimise their portfolios and refine their investment strategies. The Continuous Wavelet Transform (CWT) analysis revealed that Bitcoin could offer diversification benefits for UK stock portfolios over various timeframes; however, its correlation with stocks significantly increases during economic crises, such as the pandemic. In contrast, crude oil shows limited potential for diversifying UK indices, particularly for investment periods longer than 64 trading days, a trend evident during the 2020 pandemic. Moreover, our research indicates that gold consistently maintains a low correlation with UK indices, confirming its role as a reliable diversification tool even during global crises. Therefore, while gold remains a consistently effective diversification option, the utility of Bitcoin and crude oil varies depending on market conditions and the length of the investment period.

Our paper is structured as follows: In section two, we delve into the existing literature on Bitcoin, commodities, portfolio diversification, and stock market indices. This review provides the theoretical groundwork for our study. We also take a close look at previous studies and methods that looked at these financial assets' ability to help with risk management and diversification. This sets the stage for the empirical analysis that comes next. Section three outlines the methodologies employed to achieve our study's objectives. In section four, we present a comprehensive data analysis and empirical results. Finally, section five summarises our findings, offering insights and connecting them to the existing body of literature.

2. LITERATURE REVIEW

Markowitz (1959) Modern Portfolio Theory (MPT) remains a cornerstone in financial economics, emphasising diversification to minimise portfolio risk through reduced asset correlations. MPT posits that by evaluating the expected returns and risks of various securities, investors can construct portfolios with optimal risk-return profiles, thereby achieving better investment outcomes. Although MPT is a cornerstone in financial economics, it has been critiqued for its reliance on assumptions such as market efficiency and normally distributed returns, which frequently do not align with real-world market behaviours.

Grubel (1968) and Solnik (1974) building on MPT, demonstrated the significant benefits of international diversification, highlighting that United States (US) investors can reduce risk and improve returns by allocating capital to foreign markets. This notion was further supported by Ankrim and Hensel (1993) who argued for the superiority of commodities over real estate due to their higher liquidity. However, these studies did not account for the potential increased correlations during market crises.

Jensen, Johnson, and Mercer (2002) extended the analysis to commodity futures, finding that including a commodity index in a portfolio enhances performance due to commodities' distinct characteristics compared to stocks. Dania (2011) noted that commodities' inelastic nature helps reduce short-term volatility, yet Öztek and Öcal (2017) observed that during the 2008 financial crisis, the correlations between commodities and equities increased. This indicates that commodities might not consistently provide diversification benefits during periods of market turbulence.

Akkoc and Civcir (2019) examined the dynamic relationships between oil, gold, and the Turkish stock markets following the 2008 financial crisis. Their findings revealed significant, time-varying co-movements, highlighting the complexity of diversification strategies. This study emphasises the need to consider economic context and market-specific factors when making diversification decisions.

The COVID-19 pandemic further challenged diversification principles, as studies by Al-Awadhi, Alsaifi, Al-Awadhi, and Alhammadi (2020) and Bai, Wei, Wei, Li, and Zhang (2021) reported increased volatility and correlations among major stock markets, reducing diversification benefits. Zhang and Hamori (2021) highlighted that the long-term impact of COVID-19 on financial markets was more profound than that of the 2008 crisis, significantly affecting both stock and energy markets.

Another study by Abdullah, Abdullah, and Jaafar (2022) explored the feasibility of diversifying Islamic and conventional German stock indices with commodities such as crude oil, Bitcoin, and gold from 2011 to 2019. The findings indicated that Bitcoin's low correlation with other assets enhances diversification, although its volatility poses challenges. The authors recommended longer holding periods for gold to maximise diversification benefits.

Belanes, Saâdaoui, and Abedin (2024) investigated the diversification benefits of Islamic and conventional stock indices for US investors and their major trading partners using a Dynamic Conditional Correlations (DCC) model.

They found that Islamic indexes exhibit higher volatilities than conventional ones, with significant diversification opportunities in Japanese indexes due to low correlations with US indexes. Their study emphasises the need for understanding market correlations and suggests future research incorporating advanced analytical techniques like machine learning to optimise strategies.

Tarchella, Khalfaoui, and Hammoudeh (2024) explore the roles of oil, gold, Bitcoin, and Ethereum as safe havens, hedges, and diversifiers in G7 equity markets under various market scenarios, utilising multiple GARCH models. The study finds that gold is a reliable diversifier across all market conditions. During the COVID-19 pandemic, cryptocurrencies served as significant safe havens: Bitcoin effectively hedged stocks in G7 European countries and the UK, while Ethereum was optimal for the US and Canada. Oil demonstrates superior hedging capabilities for Japanese equity in all market conditions. The research highlights the importance of employing various GARCH models for accurate forecasting. Specifically, the GO-GARCH model is ideal for predicting the hedging roles of cryptocurrencies during stable periods. In contrast, the DCC and ADCC-GARCH models are more effective during stressed conditions, with ADCC-GARCH recommended for oil in normal markets and GO-GARCH during stress. GO-GARCH is also consistently suggested for forecasting gold's hedging role.

The literature presents mixed findings on commodity diversification, particularly during market crises, leading to an inconclusive understanding. Further research is necessary to assist investors and stakeholders in making informed portfolio decisions, given the limited studies on diversification between commodities and Islamic indices. This deeper examination is crucial to developing robust diversification strategies that withstand different market conditions.

3. METHODOLOGY

3.1. Data

This analysis utilises a comprehensive dataset encompassing daily price movements for various financial instruments. The data covers a period starting on September 1, 2011, and ending on September 30, 2022. Specific instruments include Bitcoin (represented by its exchange rate against the US dollar), crude oil, gold, the GBP/USD exchange rate, and two stock indices: the MSCI UK Islamic Index and the MSCI UK Conventional Index. Thomson Reuters DataStream provided all the data.

3.2. Time Series Techniques

This study uses a two-pronged approach to investigate the dynamic interplay between UK stock indices and other variables. A Vector Error Correction Model (VECM) is employed to explore short- and long-term relationships. Established time-series techniques are utilised to assess the temporal order (leading or lagging) between the indices and other variables. This investigation adheres to a well-defined analytical framework, building upon existing research that utilises VECM and alternative methods to examine lead-lag dynamics. This framework incorporates stationarity tests, determination of the Vector Autoregression (VAR) model order, and the application of the Johansen cointegration test. However, limitations exist in solely relying on cointegration tests to identify leading and lagging variables. VECM is therefore employed to establish Granger causality in both short- and long-term horizons (Masih, Al-Elg, & Madani, 2009). While VECM is a valuable tool, it does not provide insights into the relative direction of causal influence (endogeneity or exogeneity) between variables. Traditionally, the variance decomposition (VD) method addresses this, but our chosen statistical software (Microfit 5) restricts analysis to a maximum of 150 observations. This constraint renders VD inapplicable to our dataset containing 2,869 daily observations, as it would limit analysis to a timeframe insufficient for drawing robust conclusions. To overcome this limitation and examine lead-lag relationships across different time scales, this study utilises the Maximum Overlap Discrete Wavelet Transformation (MODWT).

Vector Error Correction Models (VECM) and variance decomposition techniques were often used together in previous research to look into lead-lag relationships between variables. These approaches generally involve cointegration tests to determine if long-term equilibrium exists among the variables. If cointegration is found, VECM is then used to analyse short-term dynamics and adjustments towards that equilibrium. This study uses VECM to investigate short- and long-term relationships between UK indices and other relevant variables. We follow established procedures, including stationarity testing, Vector Autoregression (VAR) model order selection, and the Johansen cointegration test. However, we recognise that VECM has limitations in revealing the direction of causal influence (endogeneity/exogeneity) between the variables. To address this shortcoming, we integrate MODWT with VECM, considering the restrictions imposed by our chosen software (Microfit 5) on dataset size.

3.3. Maximum Overlap Discrete Wavelet Transformation (MODWT)

By employing the Discrete Wavelet Transform (DWT) and the Maximal Overlap Discrete Wavelet Transform (MODWT), we can decompose the variance of a series into equal-sized segments using squared wavelet coefficients. We chose MODWT over DWT for decomposing a single series into various time domains due to its ability to generate more precise wavelet estimators, as demonstrated in the research of Percival (1995) and Gallegati (2008).

Whitcher, Guttorp, and Percival (2000) expanded the initial wavelet variance framework under MODWT by introducing estimators and confidence intervals for covariance and correlation. Wavelet covariance is used to evaluate the relationship between X and Y across different time scales. According to Gallegati (2008) wavelet covariance represents the covariance between X and Y at a specific scale, where the unbiased estimator is given by $\gamma_{XY,j} = \mathrm{Cov}[\widetilde{\omega}^{X}_{j,t}\widetilde{\omega}^{Y}_{j,t}]$. Additionally, $\gamma_{XY,j}$ can be calculated using the following equation, provided that the boundary conditions are satisfied.

$$\tilde{\gamma}_{XY,j} = \frac{1}{\tilde{N}_j} N - 1 \sum_{t=L_{J-1}}^{N-1} \widetilde{\omega}^{X}_{j,t}\widetilde{\omega}^{Y}_{j,t}$$

Next, the MODWT cross-correlation estimator between variable X and Y at scale J and lag τ can be represented as $\tilde{\rho}_{\tau,XY,j}$. The calculation for $\tilde{\rho}_{\tau,XY,j}$ is explained by the formulation below;

$$\tilde{\rho}_{\tau,XY,j} = \frac{\tilde{\gamma}_{\tau,XY,j}}{\tilde{\sigma}_{X,j}\tilde{\sigma}_{Y,j}}$$

The properties of the MODWT cross-correlation $\tilde{\rho}_{\tau,XY,j}$ are similar to those of the standard unconditional cross-correlation coefficient, with values ranging from -1 to 1. A coefficient approaching +1 indicates a strong positive correlation between X and Y, while a value near -1 indicates a strong negative correlation. The unique aspect of the MODWT correlation coefficient is its ability to evaluate the strength of the relationship on a scale-by-scale basis. From the spectrum $S_{\omega\, X,j}$ of wavelet coefficients at scale j, the asymptotic variance Vj of the MODWT wavelet covariance can be determined. Using the formulations provided by Gallegati (2008) a 100(1-2p)% confidence interval for the MODWT estimator, which is robust to non-Gaussianity, can be constructed for $\tilde{\upsilon}^{2}_{X,j}$. Gallegati (2008) also emphasizes the importance of having a sufficient number of wavelet coefficients, specifically Nj=128, to produce a good approximation under the large sample theory.

Studies like those by Percival (1995) and Gallegati (2008) have highlighted the accuracy of MODWT over Discrete Wavelet Transform (DWT) in producing more precise wavelet estimators. Wavelet covariance and cross-correlation estimators provide insights into relationships at different time scales. Our research leverages MODWT to evaluate lead-lag relationships across time scales, addressing the limitations of VECM and the constraints of using Microfit 5. MODWT allows for a detailed time series decomposition into various time domains, offering a more nuanced understanding of the temporal dynamics between variables.

3.4. Multivariate GARCH – Dynamic Conditional Correlation (MGARCH-DCC)

The Multivariate Generalized Autoregressive Conditional Heteroskedasticity-Dynamic Conditional Correlation (MGARCH-DCC) model, an advancement of the univariate GARCH model, plays a vital role in analysing and forecasting volatility and correlation in financial time series. This advanced model excels in determining the changing correlations between various financial instruments, making it a vital tool for portfolio management and risk analysis.

The concepts of mean and variance are at the heart of the MGARCH-DCC approach. The mean, or expected value, indicates the central tendency, which is the average projected return on a financial asset over a given period. Models such as autoregressive (AR) or moving average (MA) often calculate the mean from financial time series, which typically display non-stationarity and change their statistical properties over time. Variance, conversely, measures the spread or degree of variation in data points. In the MGARCH-DCC model, variance is employed to measure the volatility of financial assets and is modelled as a dynamic element that captures the market's fluctuating volatility.

The MGARCH-DCC model simultaneously estimates the conditional variances of each asset and their inter-asset correlations. This concurrent estimation provides a more accurate representation of the relationships between multiple financial assets. To achieve our fourth research question, we utilise the MGARCH-DCC model to examine conditional correlations between different assets. Incorporating both normal and t-distributions, we strive to enhance the precision of our findings. Following the methodology outlined by Pesaran and Pesaran (2010) we use a specific formula in the MGARCH-DCC model to compute these correlations, thereby fully leveraging the model's capabilities in understanding and managing the risks in financial markets, which can be explained as:

$$\tilde{\rho}_{ij,t-1}(\phi) = \frac{q_{ij,t-1}}{\sqrt{q_{ii,t-1}q_{jj,t-1}}}$$

Where qij,t-1 are given by

$$q_{ij,t-1} = \bar{\rho}_{ij}(1 - \phi_1 - \phi_2) + \phi_1 q_{ij,t-2} + \phi_2 \tilde{r}_{i,t-1}\tilde{r}_{j,t-1}$$

In the above equation, $\bar{\rho}_{ij}$ represents the (i,j)th unconditional correlation, while $\phi 1$ and $\phi 2$ are MGARCH-DCC parameters, with the condition that $\phi 1 + \phi 2 < 1$. The term $\tilde{r}_{i,t-1}$ denotes the standardized asset returns. To test the mean-reversion process, the study performs the computation of $(1 - \lambda i1 - \lambda i2)$. For robustness checks, several diagnostic tests recommended by Pesaran and Pesaran (2010) were conducted.

Traditional GARCH models focus on estimating conditional variances and covariances, with MGARCH-DCC models providing advancements in understanding time-varying correlations among multiple financial assets. We utilise the MGARCH-DCC model to examine conditional correlations between different assets, integrating both normal and t-distributions to enhance the robustness of our findings. By following the methodology of Pesaran and Pesaran (2010) we aim to achieve a more comprehensive analysis of volatility and correlation dynamics, which is essential for portfolio management and risk analysis.

3.5. Continuous Wavelet Transformation (CWT)

Our fifth research question can be tackled through the application of Continuous Wavelet Transformation (CWT). CWT enjoys widespread use in financial and economic studies, as demonstrated by Abdullah and Masih (2016). A key strength of CWT lies in its ability to analyse data in both the time and frequency domains simultaneously. This stands in contrast to Discrete Wavelet Transformation (DWT) or Maximum Overlap Discrete Wavelet Transformation (MODWT), which require pre-defining the number of wavelets used. CWT, on the other hand, can automatically generate appropriate scales based on the data length. Furthermore, CWT excels at mapping the correlations within the series across each time-frequency domain, significantly aiding data interpretation (Abdullah & Masih, 2016). Compared to discrete wavelet approaches, CWT analysis offers a more intuitive interpretation due to its inherent redundancy. This redundancy enhances the visibility and distinctiveness of the information within the data, ultimately leading to a more precise and user-friendly analysis.

The Daubechies (1992) wavelet filter with length L=8 is used in both Maximum Overlap Discrete Wavelet Transformation (MODWT) and Continuous Wavelet Transformation (CWT) analyses. It is written as LA (8). This specific filter offers a balance between capturing high-frequency data and generating smooth wavelet coefficients. The moderate length (L=8) of LA (8) proves effective in extracting high-frequency details from the time series data, as demonstrated by In and Kim (2013). Additionally, LA (8) outperforms other filters, such as the Haar filter, by producing smoother wavelet coefficients, facilitating a clearer interpretation of the results.

The equation for the CWT, represented as $W_X(u,s)$, is formulated by aligning a fundamental wavelet, symbolised by ψ, with the target time series $x(t)$ that resides within the $I2(R)$ space. The following mathematical formulation expresses this alignment:

$$W_X(u,s) = \infty_{-\infty} x(t) \frac{1}{\sqrt{s}} \psi \left(\frac{t-u}{s} \right) dt$$

In the specified equation, 'u' represents the time domain, while 's' denotes the frequency domain. The wavelet coherence methodology, originating from the research by Torrence and Compo (1998) is employed to analyse two separate time series:

$$R\frac{2}{n}(s) = \frac{IS\ (s^{-1} W \frac{xy}{n}(s)) I^2}{S(S^{-1} IW \frac{x}{n}(S)) I^2 S(S^{-1} IW \frac{y}{n}\ (S)) I^2}$$

In this framework, 'S' acts as a bifunctional smoothing parameter, exerting its influence across both the temporal and scale dimensions. The metric $R\frac{2}{n}(s)$, which is confined to a range from 0 to 1, as highlighted by Rua and Nunes (2009) serves as a key indicator. Values approaching 1 signal robust co-movement between the series, whereas values closer to 0 indicate a more tenuous correlation. Visual inspection of the contour plot for this metric allows for identifying areas within the time-frequency domain where the two series exhibit synchronised behaviour. This method offers a detailed examination of co-movement, considering the fluctuations and variations that occur over different times and frequencies.

Financial econometric studies extensively use CWT to map time series data into the time and frequency domain. It facilitates the analysis of correlations across various time and frequency domains without predetermining the number of wavelets. Our research employs CWT to address specific questions about the co-movement of variables. By using Daubechies (1992) least asymmetric wavelet filter with a length of L=8, we ensure the capture of high-frequency data while maintaining smoothness. This method enables a more accurate and interpretable analysis of time series data, enhancing the visibility of correlations over time.

Our methodology combines traditional techniques with advanced wavelet and GARCH models to address the limitations and constraints encountered in previous studies. By integrating VECM, MODWT, MGARCH-DCC, and CWT, we provide a comprehensive framework for analysing the dynamic relationships, volatility, and correlations among UK indices and other variables. By employing this comprehensive methodological framework, we enhance the reliability (robustness) of our results. This multi-faceted approach facilitates a richer and more insightful interpretation of the financial time series data across diverse temporal horizons (time scales).

4. EMPIRICAL RESULTS

4.1. Descriptive Data

Figure 1 depicts the raw time series data for all chosen variables. The plot reveals the pronounced volatility exhibited by Bitcoin prices, particularly during the COVID-19 pandemic period spanning 2020 to 2022. Oil and gold prices have also fallen, showing a lack of demand for these goods before the epidemic. After that, the prices of both commodities rose sharply, indicating that gold and crude oil were highly sought-after during times of crisis. Meanwhile, both the UK Islamic and conventional indices were in a downtrend before COVID-19 and fell off sharply in 2020 at the early stage of the pandemic. However, it soon recovered. When the Russia-Ukraine conflict began in 2022, the stock indices declined again, along with the exchange rate of British Pound/US Dollar (GBPUSD). This suggests that time of crisis significantly impact the stock indices.

Table 1 provides a summary of the key statistical properties of the daily return series for six financial instruments. The return series, denoted by rt, is calculated as the natural logarithm of the price ratio between consecutive time periods (Pt/Pt-1), where Pt represents the price index at time t. The variables included in the table are the UK Islamic Index (UKIS), UK Conventional Index (UKCON), gold, oil, GBP/USD exchange rate, and Bitcoin. Descriptive statistics presented for each variable include the mean, standard deviation, minimum value, maximum value, skewness, kurtosis, and the total number of observations. The mean return for Bitcoin is notably higher compared to the other variables, suggesting its higher return potential. However, Bitcoin also demonstrates the highest standard deviation and maximum value, indicating significantly greater volatility relative to other assets, making it a riskier investment.

Additionally, skewness and kurtosis values for each variable offer insights into the distribution shape of their returns. Skewness measures the asymmetry of the distribution, with negative skewness indicating a longer tail to the left and positive skewness indicating a longer tail to the right. The kurtosis value reveals the thickness of the distribution's tails, with higher values indicating thicker tails and a higher likelihood of extreme events. Overall, the descriptive statistics in this table allow for comparing the risk-return profiles of different assets and offer insight into their respective return distributions.

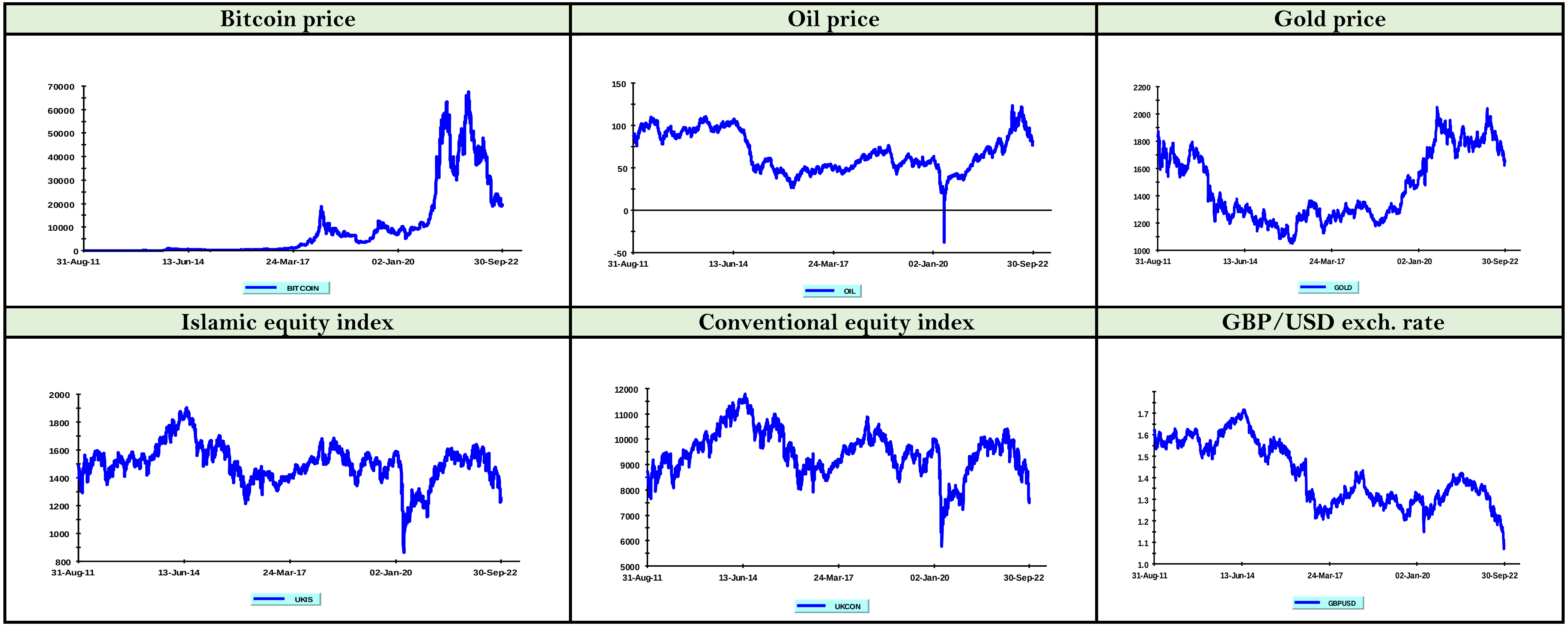

Figure 1. Dynamics of raw time-series data.

Table 1. Descriptive statistics.

Variable	Mean	Standard deviation	Min.	Max.	Skewness	Kurtosis	Number of observations
UKIS	-0.000	0.013	-0.157	0.132	-0.864	16.267	2,869
UKCON	-0.000	0.012	-0.135	0.105	-0.994	13.978	2,869
GOLD	-0.000	0.010	-0.098	0.058	-0.598	6.998	2,869
OIL	0.000	0.027	-0.282	0.320	0.096	26.154	2,869
GBPUSD	-0.000	0.006	-0.084	0.030	-1.337	20.128	2,869
BITCOIN	0.003	0.056	-0.664	0.485	-0.873	19.757	2,869

4.2. Empirical Results of Standard Time-Series Techniques

Our time series regression analysis commences with investigating the order of integration for each variable. Employing Augmented Dickey-Fuller (ADF) tests, we establish that all chosen variables exhibit integration of order 1, denoted as I (1). To determine the optimal lag length for the Vector Autoregression (VAR) model, we utilise both the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC). Both criteria converge on a lag order of one.

The Vector Error Correction Model (VECM) analysis is subsequently employed to investigate the variables' causal relationships and direction of influence. As presented in Table 2, our findings suggest that crude oil and the GBP/USD exchange rate exhibit exogenous behaviour, while the UK stock indices, Bitcoin, and gold display endogenous characteristics. This implies that fluctuations in crude oil and GBP/USD potentially influence the movements of the UK stock indices, Bitcoin, and gold prices. Furthermore, VECM analysis differentiates between long-term and short-term causal relationships (Granger causality). The error correction term (εt-1) within the VECM captures the significance of long-term co-movements. The F-statistic can assess the joint influence of short-term lagged variables, while individual short-term effects can be analysed separately. To ensure the validity of the estimated model, diagnostic tests for autocorrelation, heteroskedasticity, and functional form are conducted using the Error Correction Model (ECM) residuals.

Table 2 reports the estimated Error Correction Model (ECM) equations for the UK indices alongside other variables. Additionally, the table presents various diagnostic statistics to assess the model's validity. These statistics include chi-squared tests for serial correlation, functional form misspecification, normality of residuals, and heteroskedasticity. Standard errors (SEs) are provided in parentheses for each coefficient estimate. The results generally indicate a well-specified model, with asterisks denoting statistical significance at the 5% level. However, the variance decomposition analysis, traditionally employed to quantify a variable's exogeneity and endogeneity based on past shocks, was not feasible due to software limitations. Our dataset encompasses 2,869 daily observations, exceeding our chosen software's maximum capacity (150 observations) (Microfit 5). To address this constraint and accurately determine the lead-lag relationships among the variables, we implemented the Maximal Overlap Discrete Wavelet Transform (MODWT).

Table 2. Error correction model for UK indices and other variables.

Dependent variable	DBitcoin		DOil		DGold		DUKis		DUKconv		DPousd	
ECM (-1)	-0.00993	(0.0035)	1.1593	(0.0007)*	-2.1377	(0.0005)	0.00208	(0.0005)	0.00201	(0.0004)	4.88E-05	(0.0002)*
Chi - square SC(1)	4.1963	(0.041)	7.8658	(0.005)	5.1532	(0.023)	0.67253	(0.412)	2.3482	(0.125)	0.41564	(0.519)
Chi - square FF(1)	1.1195	(0.290)	1.6993	(0.192)	0.22661	(0.634)	1.345	(0.246)	1.535	(0.215)	0.86991	(0.351)
Chi - square N(2)	10693	(0.000)	834.52	(0.000)	2069.6	(0.000)	425.986	(0.000)	333.9066	(0.000)	32.8642	(0.000)
Chi - square Het(1)	4.9065	(0.027)	2.8024	(0.094)	9.2118	(0.002)	23.7342	(0.000)	30.4831	(0.000)	1.6846	(0.194)

Note: Standard errors (SEs) are provided in parentheses. Diagnostic tests include chi-squared statistics for serial correlation (SC), functional form (FF), normality (N), and heteroskedasticity (Het). Consequently, the equations are generally well-defined. An asterisk (*) indicates significance at the 5% level. DUK is represents the UK ISIR, and DUKconv represents the UK CSIR.

4.3. Empirical Results of MODWT

Figure 2 illustrates the wavelet cross-correlation analysis between crude oil price returns and GBP/USD exchange rate returns using the MODWT. The figure shows the correlations across multiple time scales, along with their approximate 95% confidence intervals. Each cross-correlation function corresponds to a specific wavelet scale (λ), where λ_1 represents a time scale of approximately 1-2 days, λ_2 represents 2-4 days, continuing similarly, with λ_8 representing the longest time scale of 128-256 days. The red lines indicate the 95% confidence interval for the wavelet cross-correlation values.

The plotted curve within the figure serves to visualise the lead-lag relationship between the two variables. Suppose the curve exhibits statistically significant values on the left side of the y-axis, exceeding the 95% confidence interval (depicted by the red lines). This indicates that the first variable leads the second variable at the corresponding time scale (represented by the λ values on the x-axis). Conversely, significant values on the right side of the y-axis exceeding the confidence interval suggest that the second variable leads the first variable at that particular time scale. The curve's position relative to horizontal axis reflects the strength and direction (positive or negative) of the correlation. Positive values above the axis indicate a positive correlation, while values below the axis signify a negative correlation.

An examination of Figure 2 reveals the following insights regarding the lead-lag relationship between crude oil prices and GBP/USD exchange rates across different time scales:

- Wavelet levels 1, 2, and 3: The wavelet cross-correlation curve in these ranges exhibits no statistically significant bias towards either left or right side of the y-axis. This suggests an inconclusive lead-lag relationship at these shorter time scales (approximately 1-8 days based on the λ values).
- Wavelet levels 4, 5, and 7: The curve displays a rightward slant at these levels, exceeding the 95% confidence interval on the positive side of the y-axis. This indicates that GBP/USD exchange rate fluctuations likely lead to crude oil price movements at the corresponding time scales (between 8-64 days).
- Wavelet levels 6 and 8: The curve exhibits a positive skew toward the left side of the y-axis at these levels, with values exceeding the confidence interval. This suggests that crude oil prices likely lead GBP/USD exchange rates at the corresponding longer time scales (between 64-256 days).

At lower wavelet levels (4 and 5), the GBP/USD exchange rate precedes movements in crude oil prices; at higher wavelet levels (6 and 8), crude oil prices precede movements in the GBP/USD exchange rate. This suggests that for time frames shorter than 64 days, crude oil prices react to changes in the GBP/USD exchange rate, while for periods longer than 64 days, the GBP/USD exchange rate responds to changes in crude oil prices. This lead-lag relationship highlights the potential for diversification benefits both in the short and long term.

Despite the UK being a net importer of crude oil and heavily dependent on it for energy, it is also one of Europe's leading oil and gas producers. Income from the energy sector greatly influences the UK's balance of payments, and over time, crude oil prices can significantly impact GBP/USD exchange rate. Thus, it can be concluded that crude oil prices substantially impact the GBP/USD exchange rate.

4.4. Empirical Results of MGARCH-DCC

The research used the MGARCH-DCC model to assess the diversification benefits of the selected variables. Table 3 presents the Maximum Likelihood Estimators (MLE) for λ_i1 and λ_i2 related to commodity price fluctuations and stock indices, as well as δ_1 and δ_2 for two distributions: the multivariate normal and the multivariate Student t-distribution. The results showed a higher log-likelihood value for the t-distribution [54225.4] compared to the normal distribution [53470.8]. The estimated degrees of freedom were below 30, indicating that the t-distribution better captures the fat-tailed nature of stock returns. Therefore, the subsequent analysis used the estimates from the t-distribution.

Table 3 also underscores the significance of the asset-specific volatility decay parameters, labelled λ1 and λ2, as evidenced by the substantial t-ratios. These results suggest a tendency for asset volatility to revert to its mean. Specifically, the combined estimated volatility decay parameters for Bitcoin, which include Lambda1 (λ1) and Lambda2 (λ2), total 0.98499 (0.87508 + 0.10991). Since this value is less than 1, it indicates that any volatility shock is temporary and will likely return to its average level. This pattern is consistent across Bitcoin, other stock indices, and commodity price returns examined in this study. The study's outcomes indicate that while the volatility of the analysed asset returns can fluctuate with market dynamics, they generally revert to their average over longer periods.

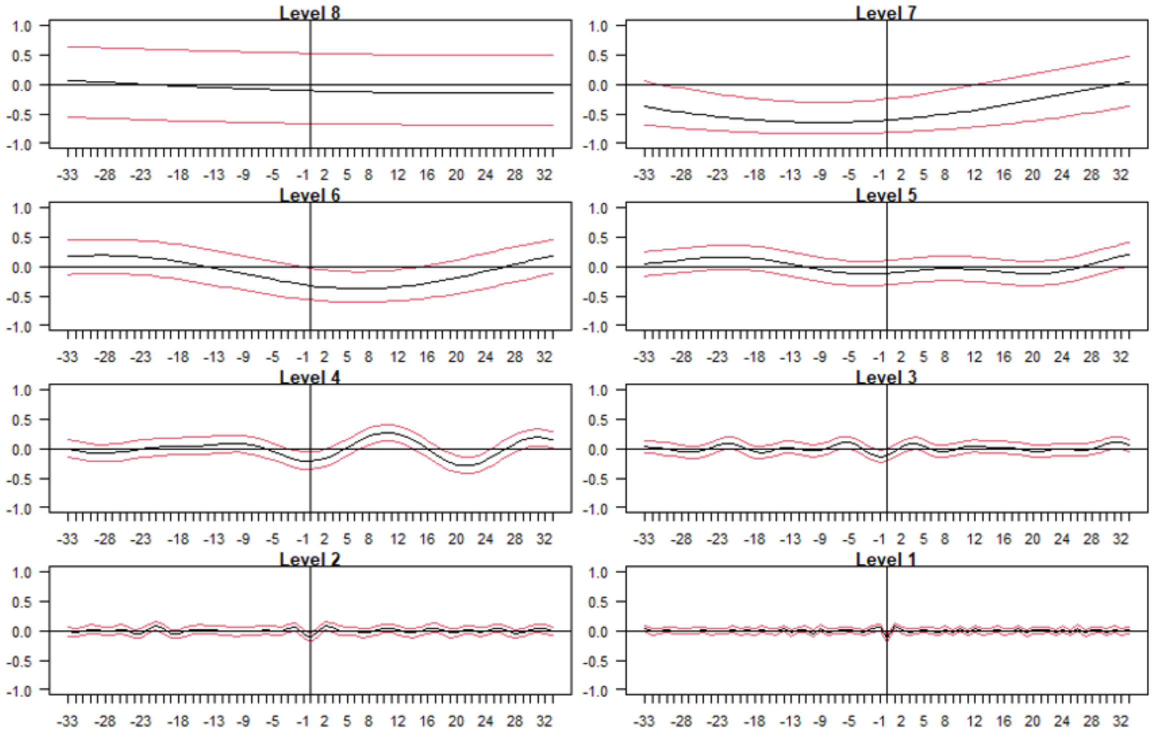

Figure 2. MODWT analysis of crude oil price return and GBP/USD exchange rate return.

Table 3. Assessments of the six variables.

		Multivariate normal distribution			Multivariate *t* distribution		
	Variables	**Estimate**		**T-ratio**	**Estimate**		**T-ratio**
Lamda 1 (λ1)	Bitcoin	0.875		62.991	0.854		58.222
	Oil	0.872		75.450	0.888		72.549
	Gold	0.941		81.019	0.970		182.493
	UKis	0.905		89.012	0.936		98.991
	UKconv	0.895		77.801	0.930		91.331
	GBPUSD	0.877		54.742	0.944		77.985
Lamda 2 (λ2)	Bitcoin	0.110		9.830	0.136		10.526
	Oil	0.093		12.050	0.078		9.640
	Gold	0.046		5.912	0.027		6.400
	UKis	0.065		10.949	0.043		7.696
	UKconv	0.071		10.705	0.048		7.775
	GBPUSD	0.081		9.579	0.035		5.400
Delta 1 (δ1)		0.917		96.842	0.925		86.576
Delta 2 (δ2)		0.026		12.388	0.022		10.425
Maximised log-likelihood			53470.800			54225.400	
Degree of freedom (df)			-			6.955	

Note: λ_1 and λ_2 represent decay factors for variance and covariance, respectively. UKis refers to the UK ISIR, and UKconv refers to the UK CSIR.

Table 4 illustrates a projected matrix of unconditional volatilities for various UK stock indices returns alongside other variables. The diagonal elements display the estimated unconditional volatilities, while the off-diagonal elements indicate unconditional correlations. The values within the diagonal elements' parentheses denote the highest to lowest volatility rank. From the estimates in Table 4, it is evident that Bitcoin prices experience greater volatility compared to other variables, indicating a market with higher speculative activity. Conversely, the GBP/USD exchange rate exhibits the lowest volatility, reflecting a stable economy and currency. Overall, the matrix provides essential insights into the volatility and correlation levels among different variables, aiding investors and analysts in making well-informed decisions regarding investment opportunities and risk assessment.

Table 5 presents a ranking of unconditional correlations between commodity prices and stock indices, addressing the third research objective. The table lists correlation ranks from highest to lowest, organised from left to right and top to bottom. Table 5 provides several key insights. The Bitcoin price return, indicated by an '*', shows the lowest correlation with other variables, suggesting that including Bitcoin in a portfolio can provide diversification benefits. However, as indicated in Table 4, Bitcoin is also the most volatile asset. Therefore, investors seeking stability might consider gold a more reliable diversification instrument to avoid high risk and uncertainty. Worthington and Pahlavani (2007) note that gold serves as a near-perfect hedge against inflation. For investors preferring high volatility, Bitcoin remains a suitable diversification tool. Gold, traditionally a safe haven and hedging instrument, is less volatile than Bitcoin, as demonstrated in Table 4. The correlation between gold and the UK stock indices is also the second lowest in Table 5, highlighting the diversification benefits of including gold in a portfolio. Furthermore, gold can serve as an effective inflation hedge. Investors in crude oil should also consider gold for diversification, as the correlation between these two variables is the second lowest in Table 5.

The GBP/USD exchange rate return has the lowest correlation with the Bitcoin price return, as shown in Table 5. Thus, investors holding GBP/USD investments can benefit from adding Bitcoin to their portfolios for diversification. This finding also suggests Bitcoin's potential as an alternative currency to the pound sterling, as it can be used as a hedging instrument against speculative attacks on the pound. In summary, Table 5 offers valuable insights into the relative correlation ranks among various variables, guiding investors in making informed decisions when constructing diversified portfolios or assessing risk.

Table 4. Projected unconditional volatility matrix for UK stock indices returns and other variables.

	UKis	Rank	Ukconv	Rank	Gold	Rank	Oil	Rank	Gbpusd	Rank	Bitcoin	Rank
Ukis	0.013	(3)	0.938		0.161		0.361		0.416		0.113	
Ukcon	0.938		0.012	(4)	0.114		0.316		0.523		0.103	
Gold	0.161		0.114		0.010	(5)	0.125		0.201		0.065	
Oil	0.361		0.316		0.125		0.027	(2)	0.141		0.060	
Gbpusd	0.416		0.523		0.201		0.141		0.006	(6)	0.042	
Bitcoin	0.113		0.103		0.065		0.060		0.042		0.055	(1)

Table 5. Hierarchical order of unconditional correlations among returns of UK stock indices and additional variables.

UK ISIR		UK CSIR		Gold		CRUDE OIL		POUND/USD		BITCOIN
(UKIS)		UKCON		(GOLD)		(OIL)		(GBPUSD)		(BITCOIN)
UKCONV		UKIS		GBPUSD		UKIS		UKCON		UKIS
GBPUSD		GBPUSD		UKIS		UKCON		UKIS		UKCON
OIL		OIL		OIL		GBPUSD		GOLD		GOLD
GOLD		GOLD		UKCON		GOLD		OIL		OIL
BITCOIN	*	BITCOIN	*	BITCOIN	*	BITCOIN	*	BITCOIN	*	GBPUSD

Note: * indicates the lowest correlation of the variable with the first-row of the corresponding variable.

Our previous analyses of volatilities and correlations were conducted on an unconditional basis, using average calculations. However, assuming constant volatility and correlation values over an eleven-year period is unrealistic. To address this, we employ the Dynamic Conditional Correlation (DCC) model, which accounts for the dynamic nature of volatility and correlation. The first step is to examine the temporal aspect of volatility. Figures 3 and 4 depict the conditional volatilities for six variables over eleven years. During this period, Bitcoin price returns showed the highest volatility compared to other variables, while the GBP/USD exchange rate exhibited the least volatility. This finding is consistent with our previous results in Table 4. Bitcoin's return volatility is significantly higher and more unpredictable than other variables over the eleven years, highlighting its riskiness for investors. However, for those seeking high-volatility investments, Bitcoin remains an attractive option. Conversely, the GBP/USD exchange rate remains stable, followed by gold, UK CSIR, and ISIR, as shown in Figure 4. This stability suggests that UK indices are reliable, reflecting economic steadiness and regional robustness.

We also observed that all variables exhibited significant volatility at the onset of the COVID-19 pandemic, underscoring the market uncertainty caused by it. Crude oil was the most volatile asset during this period, experiencing dramatic fluctuations due to widespread market uncertainty and panic. The shutdown of numerous factories and facilitates during the pandemic caused the extreme volatility in crude oil. Interestingly, none of the variables displayed signs of instability during the Russia-Ukraine conflict, indicating that the pandemic substantially impacted market volatility more than the war.

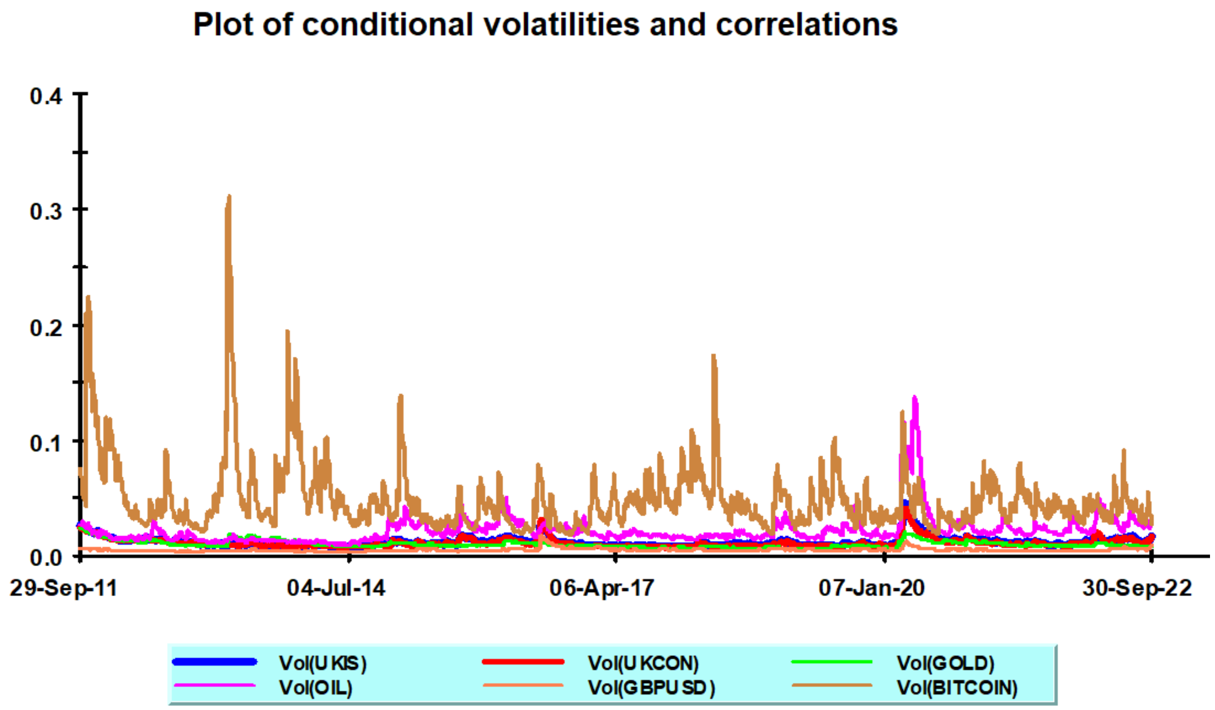

Figure 3. Conditional volatilities of UK stock indices returns and other variables.

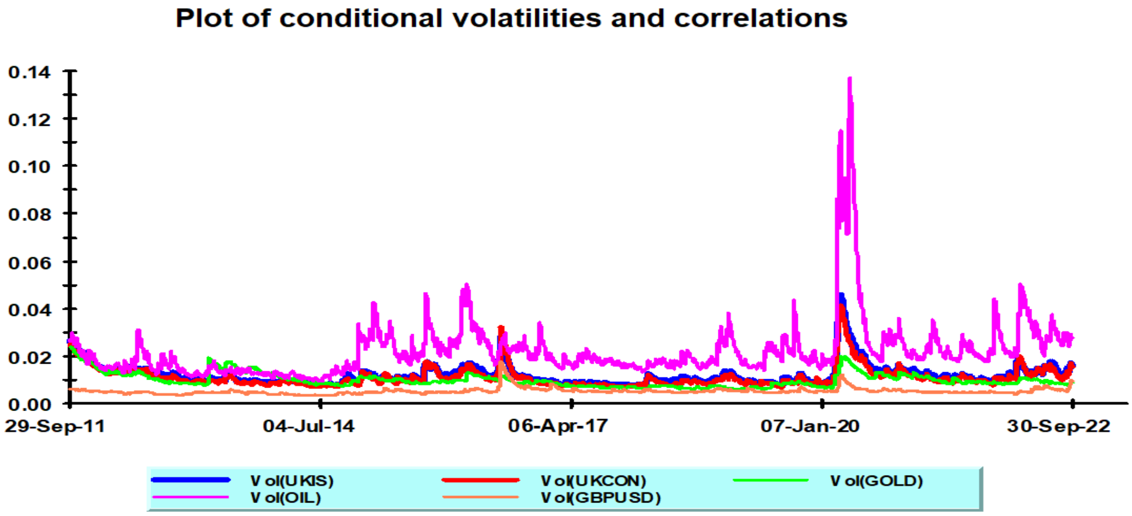

Figure 4. Conditional volatilities of UK stock indices returns and other variables (Excluding bitcoin).

We continue our analysis by examining the conditional correlations between Bitcoin price returns and UK Islamic and conventional stock indices, as illustrated in Figure 5. Between 2011 and 2014, the correlation between Bitcoin and UK stock indices returns declined. However, this correlation increased from 2014 to 2022, indicating a potential diversification benefit reduction between Bitcoin and UK stock indices. It is noteworthy that the correlation between the UK Islamic stock index returns and Bitcoin price returns is slightly higher than that of the conventional stock index, suggesting that the conventional index might provide superior portfolio diversification. Between 2013 and 2018, there were periods where the indices and Bitcoin had a negative correlation, indicating that Bitcoin could serve as a hedging mechanism. However, this negative correlation was inconsistent, suggesting some instability in the relationship. Consequently, investors should be cautious when considering Bitcoin as a hedging tool. The correlation between the indices and Bitcoin became more closely aligned after the pandemic outbreak in 2020, indicating that these variables responded similarly to pandemic-related news. Investors should consider historical and current trends in correlations when diversifying their portfolios. It is essential to remember that correlations are dynamic and can change over time, as demonstrated by the relationship between Bitcoin and UK stock indices. Additionally, investors should carefully evaluate the risks and volatility associated with each asset before incorporating them into their portfolios, considering their investment objectives and risk tolerance.

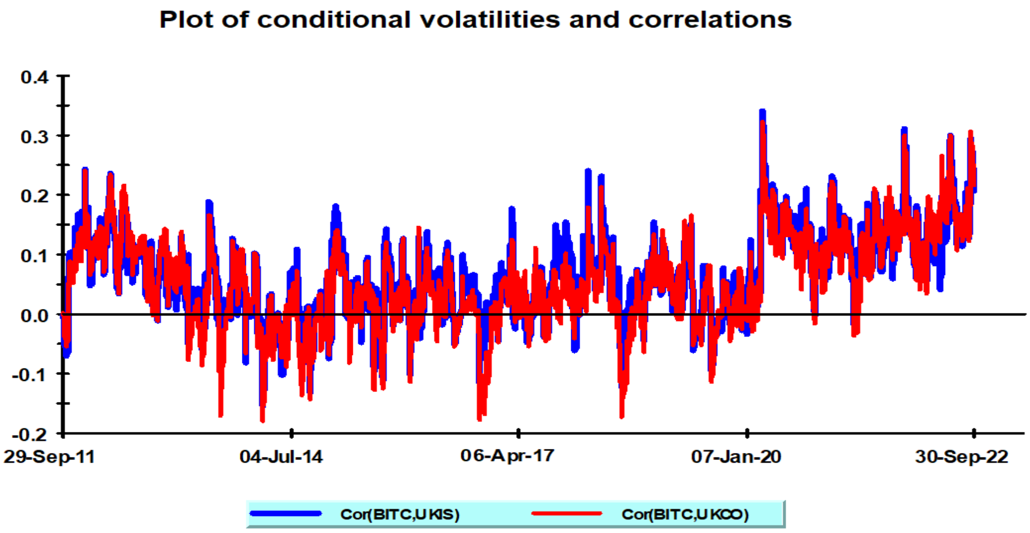

Figure 5. Conditional correlation between bitcoin (BITC) price returns and UK Islamic (UKIS) and conventional (UKCO) stock indices returns.

Table 5 indicates that crude oil prices have the highest correlation with UK stock indices, suggesting they might not be ideal for portfolio diversification. However, Figure 6 shows an intriguing trend in the correlation between these variables from 2011 to 2020, where the correlation has declined, hinting at potential diversification benefits if this trend persists. Investors interested in crude oil and UK indices should consider this trend and exercise caution in their investment decisions. The correlation between these variables spiked during the 2020 pandemic, indicating a similar response to the negative news of COVID-19. Conversely, when the Russia-Ukraine conflict began in 2022, the correlation between the indices and crude oil decreased, suggesting potential diversification benefits if the downtrend continues. Therefore, investors should closely monitor the correlation trend between crude oil and UK stock indices and make informed investment decisions accordingly. Although these variables might not be the optimal choices for portfolio diversification the moment, investors should not disregard the potential for future diversification advantages.

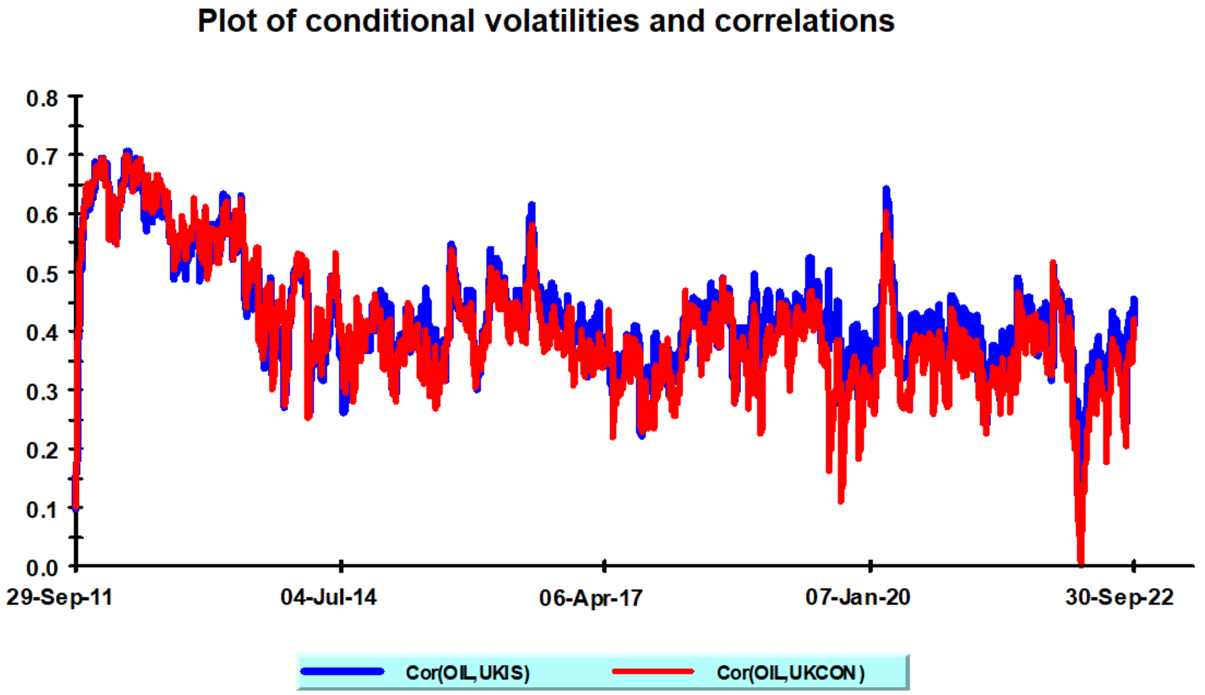

Figure 6. Conditional correlation of crude oil price return with United Kingdom Islamic (UKIS) and conventional (UKCO) stock indices return.

The findings in Table 5 indicate that gold price returns exhibit the second lowest correlation with the UK conventional index. This implies that investors holding a gold portfolio might achieve greater diversification benefits with the UK CSIR compared to the UK ISIR, due to the higher volatility and correlation of the UK ISIR relative to the UK CSIR. Figure 7 shows a downward trend in the correlation between gold and UK stock indices returns from 2011 to 2020. However, this trend started to reverse in 2020 with the onset of the pandemic, and the correlation significantly decreased during the Russia-Ukraine conflict. This implies a heightened potential for diversification benefits between the returns of gold prices and the UK stock indices. Furthermore, from 2020 onwards, periods of negative correlation between gold and the indices emerged, offering hedging opportunities. Nevertheless, the inconsistency of the negative correlation indicates that gold may not be as reliable a safe haven and hedging instrument as it once was. Therefore, investors should exercise caution when considering gold as a hedging tool. Despite this, the overall downward trend in the correlation between gold and UK stock indices returns suggests that gold could still offer diversification benefits to a portfolio, especially when combined with other assets that have different risk and return profiles.

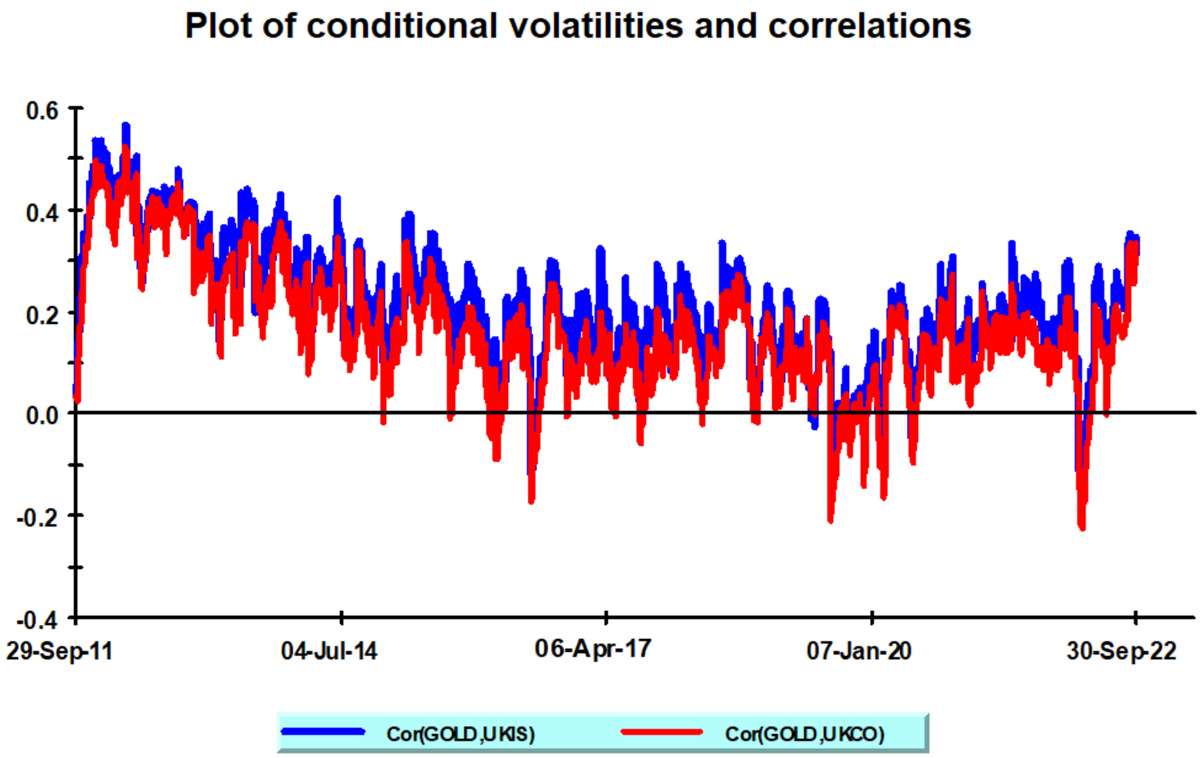

Figure 7. Conditional correlation of gold price return with United Kingdom Islamic (UKIS) and conventional (UKCO) stock indices return.

4.5. Empirical Results of CWT

This research employs the Continuous Wavelet Transform (CWT) technique to accomplish our fourth research objective, as demonstrated in Figures 8–13. These figures present the estimated CWT values across different wavelet scales, from scale 1 (1-2 days) to scale 8 (2 years of trading days). The horizontal axis represents the number of trading days, while the vertical axis denotes the investment intervals. The results of the Monte Carlo simulation establish a 5% significance level, illustrated by the curve line below. The color codes indicate the correlation between various variables, with blue representing low correlation and red indicating high correlation. The wavelet method allows for an analysis of the relationship between UK indices and other variables, aiding investors in portfolio diversification.

Figures 8 and 9 show that investors holding portfolios comprising UK conventional, Islamic stock indices, and Bitcoin can benefit from diversification across various holding periods. Bitcoin and UK indices generally do not show significant short- and long-term correlations, except for holding periods over 256 days between 2020 and 2022. Nonetheless, there is a high correlation between these variables during pandemic and conflict periods due to the rapid fluctuations in Bitcoin prices. Consequently, investors can utilise this information to diversify their portfolios while effectively managing risk.

For a portfolio containing crude oil and UK stock indices, holding the portfolio for no more than 64 trading days is recommended to maximise diversification benefits, as depicted in Figures 10 and 11. The correlation between crude oil and the UK ISIR is slightly higher than that of the UK CSIR due to the higher concentration of energy sector companies in the UK ISIR. In contrast, the UK CSIR includes companies that are less sensitive to oil price fluctuations, providing greater diversification. Given that the UK is a net importer of crude oil for energy consumption, fluctuations in crude oil prices can expose the UK economy to vulnerabilities. As the largest crude oil exporter in the European region, the UK's balance of payments heavily depends on crude oil. During the 2020 pandemic, the correlation between indices and crude oil was the strongest compared to Bitcoin and gold, particularly for investments exceeding 128 days. This suggests that crude oil and indices are less effective for diversification during such periods. The study's finding that crude oil and UK indices are unsuitable for diversification during the pandemic contrasts with some previous research that identified crude oil as a beneficial diversification asset, even during market stress (Narayan, 2022). This discrepancy may be due to the unique economic context of the UK as a net importer of crude oil.

Figures 12 and 13 demonstrate that investors can attain diversification benefits before the 256-day holding period by including UK indices and gold in their portfolios, as the correlation between these assets remains low at shorter scales. However, for periods beyond 256 to 300 days, the correlation between the two variables increases significantly for both indices, diminishing the long-term diversification benefits. Figure 13 also validates that the correlation between the UK CSIR and gold aligns with the findings in Table 5, showing that these variables have a low correlation and can be effectively utilised for portfolio diversification. The pandemic and the Russia-Ukraine conflict have had minimal impact on the correlation between UK indices and gold, confirming gold as a reliable diversification asset for both Islamic and conventional indices.

Table 6. Month and years for horizontal axis.

Horizontal axis	Month and Years
500	August 2013
1000	July 2015
1500	June 2017
2000	May 2019
2500	May 2021

Table 6 presents the timeline for the wavelet analysis, indicating specific months and years that correspond to the horizontal axis labels in Figures 8 to 13. This timeline helps interpret the temporal scope of the data and the identified patterns.

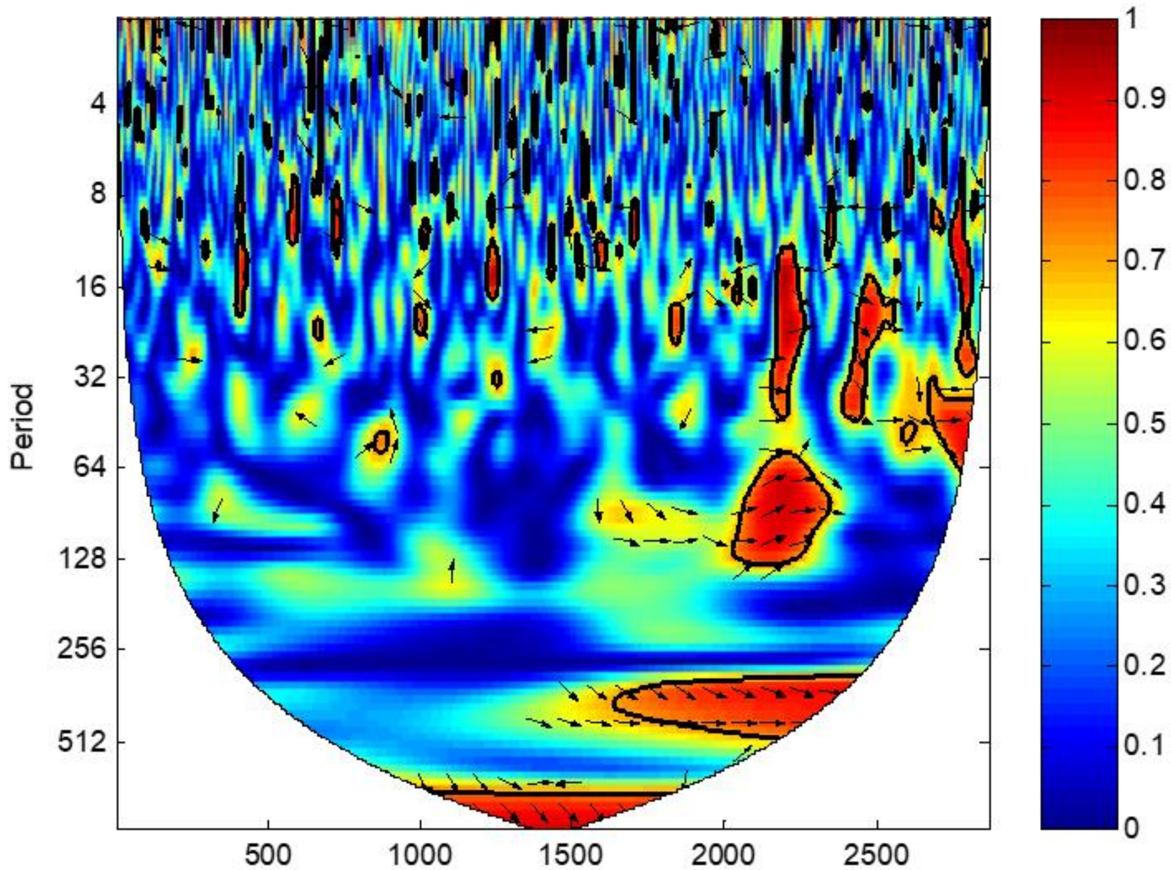

Figure 8. CWT – bitcoin price return vs UK Islamic stock index return.

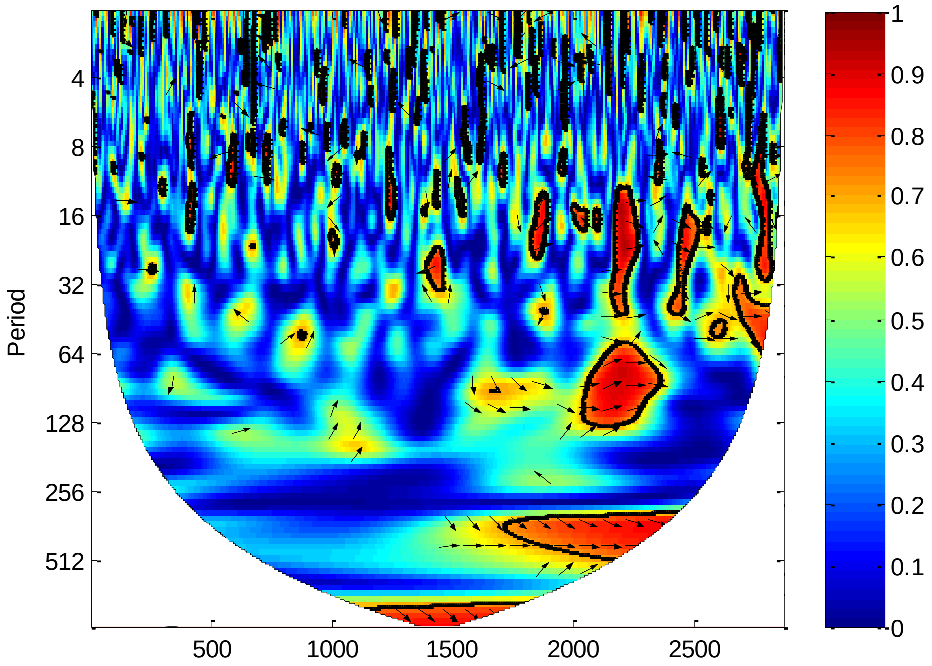

Figure 9. CWT – Bitcoin price return vs UK conventional stock index return.

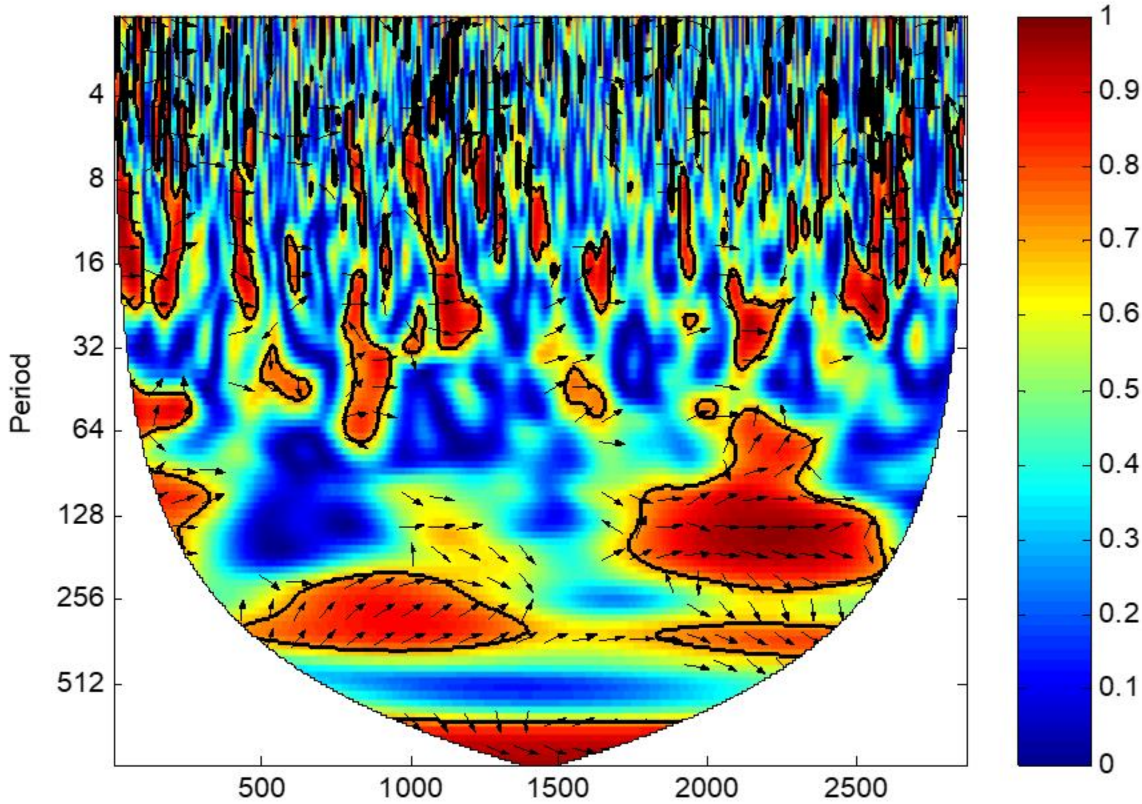

Figure 10. CWT – crude oil price return vs UK Islamic stock index return.

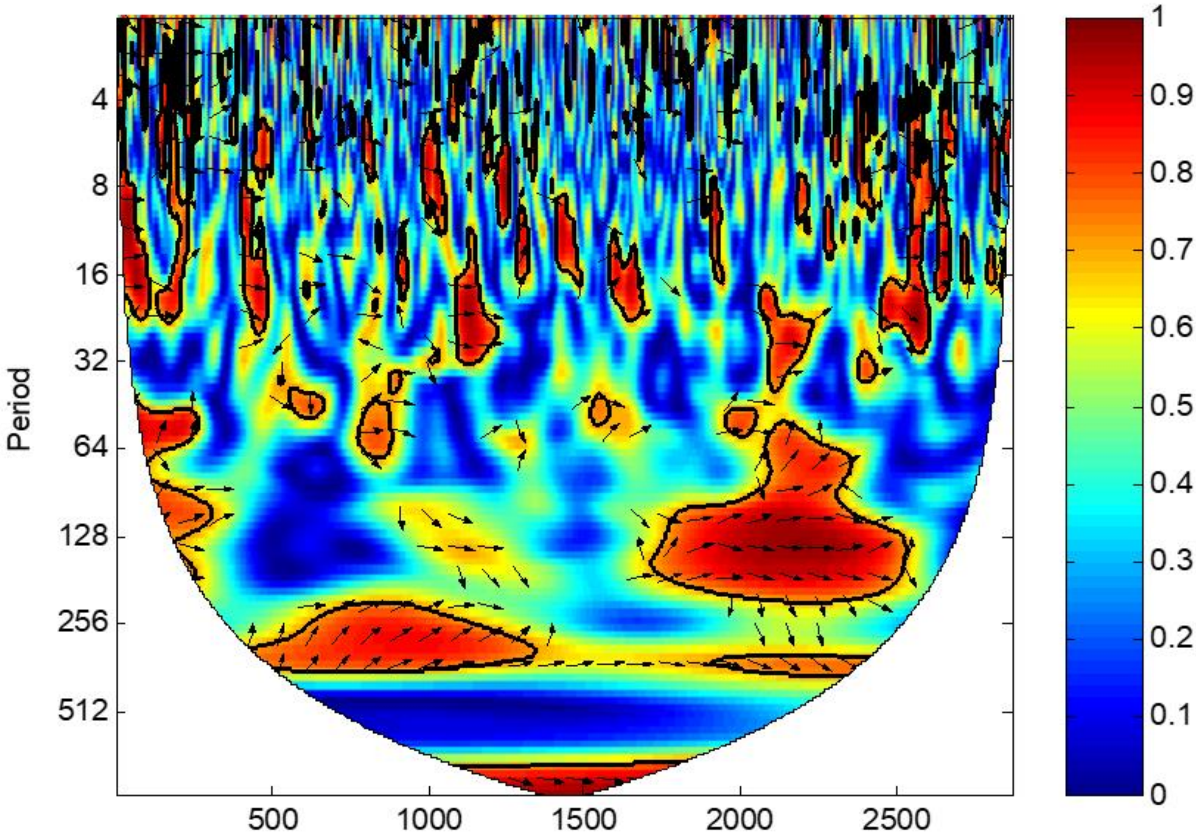

Figure 11. CWT – crude oil price return vs UK conventional stock index return.

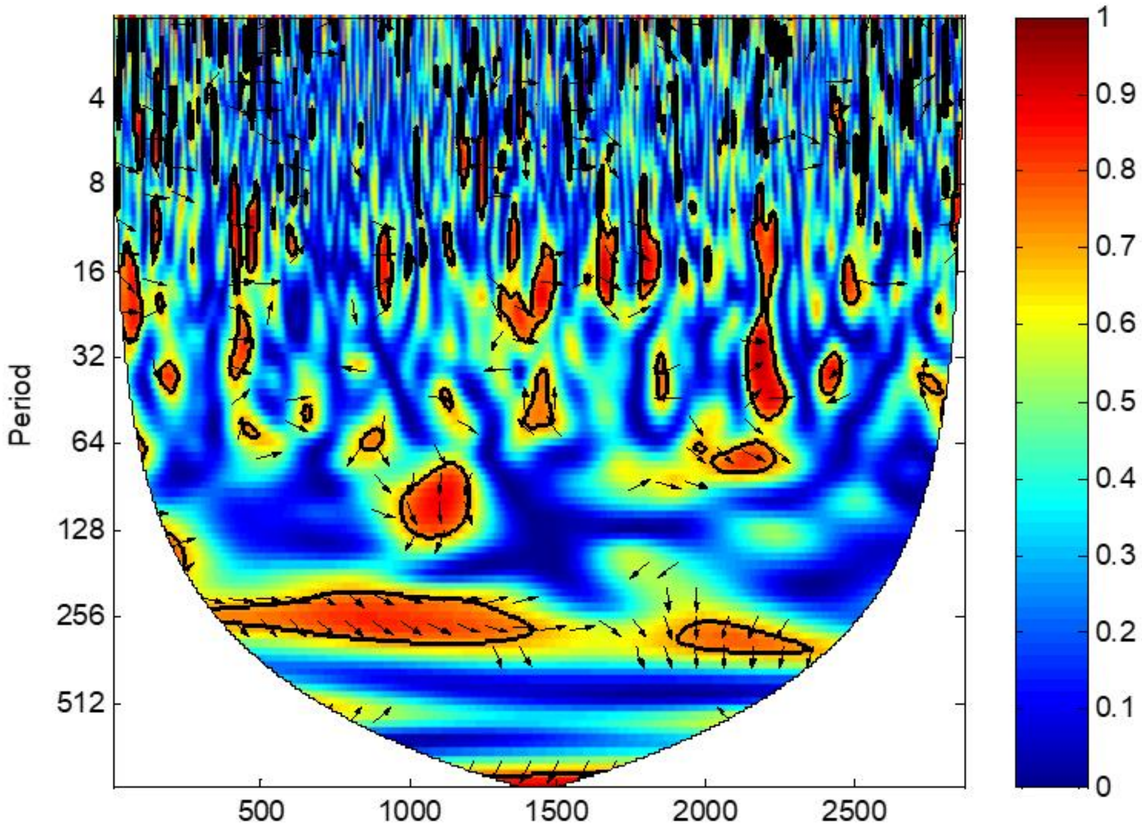

Figure 12. CWT – gold price return vs UK Islamic stock index return.

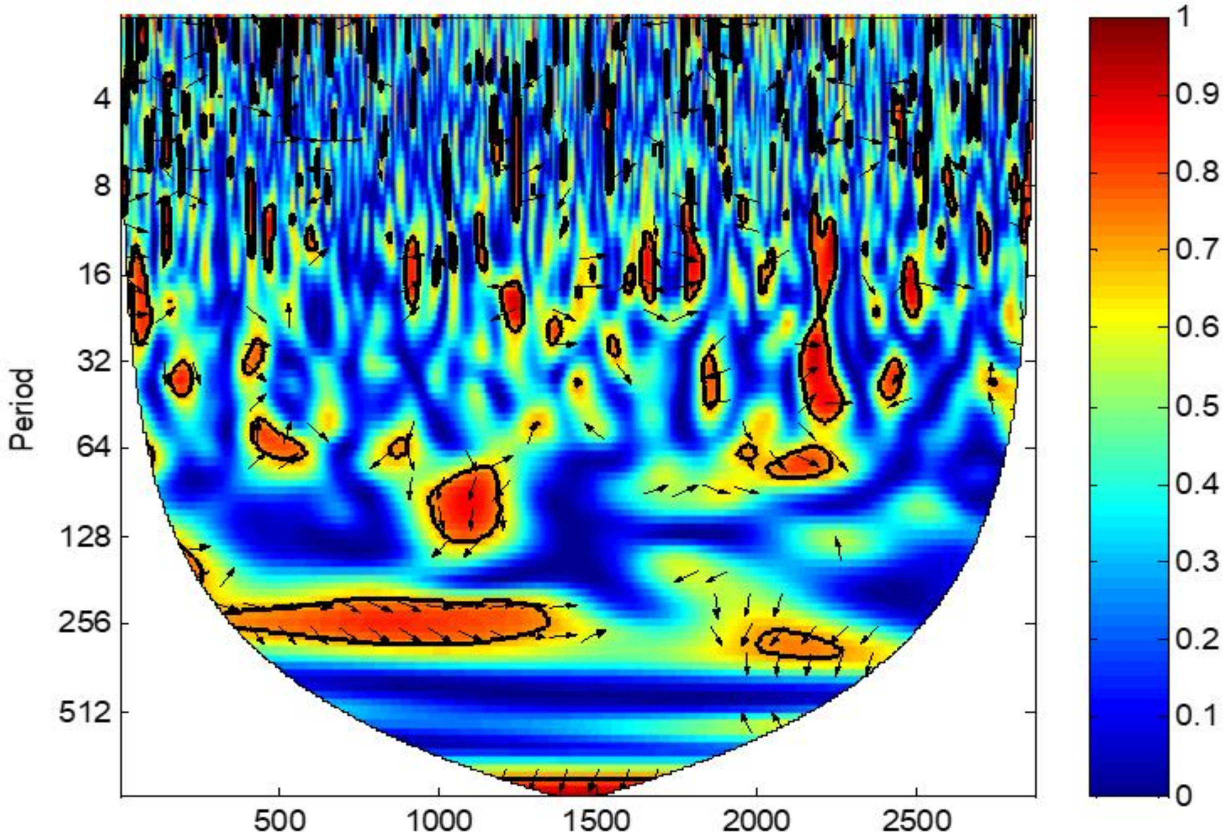

Figure 13. CWT – gold price return vs UK conventional stock index return.

5. CONCLUSION

This study looked at how conventional and Islamic stock indices in the UK could be used to diversify, along with Bitcoin, gold, crude oil prices, and the GBP/USD rate. It did this using methods like VECM, MODWT, MGARCH-DCC, and CWT from 1 September 2011 until 30 September 2022. Our findings address several key research questions. The VECM findings show that while crude oil price returns and GBP/USD exchange rate returns are exogenous, variables like UK indices, gold, and Bitcoin are endogenous, meaning they react to shifts in crude oil prices and GBP/USD rates. This dynamic causal relationship highlights the influence of these commodities on stock index returns.

The analysis demonstrates that historical values of stock indices can predict commodity price movements to some extent. The MODWT-based wavelet cross-correlation indicates that crude oil and GBP/USD are identified as exogenous variables across various time horizons, exhibiting greater exogeneity compared to other variables. GBP/USD leads crude oil prices at medium scales, while crude oil prices lead GBP/USD at longer scales. Results from MGARCH-DCC indicate that investors should focus on GBP/USD and crude oil for diversification benefits, as they show a low correlation with UK indices. Bitcoin also shows potential as a diversification tool, but its high volatility remains a concern. In line with Smales (2019) perspective, we concur that Bitcoin's status as a safe haven is yet to be established, whereas gold, given its historically lower correlation with indices, stands as a preferable diversification tool. Contrary to Fabris and Ješić (2023) our research pinpoints gold's safe haven attributes to specific intervals. Even during global disruptions, such as the 2020 pandemic and the 2022 Ukraine-Russia conflict, gold's correlation with UK indices remained low, while Bitcoin and crude oil prices exhibited parallel price return movements. The analysis from CWT revealed that while Bitcoin offers diversification benefits for UK stock portfolios over various periods, its correlation increases significantly during economic uncertainties like the pandemic. Conversely, crude oil shows limited diversification potential with UK indices for holding periods beyond 64 trading days, particularly during the 2020 pandemic. Our findings also indicate that gold consistently presents a low correlation with UK indices, maintaining its status as a reliable diversification asset even during global crises. This suggests that gold remains a stable tool for portfolio diversification, whereas Bitcoin and crude oil's effectiveness varies with market conditions and holding periods. The increased correlation between Bitcoin, crude oil, and UK indices during the pandemic and conflict periods is consistent with the literature that documents how extreme market conditions can increase correlations among asset classes, reducing the benefits of diversification (Akhtaruzzaman, Boubaker, & Sensoy, 2021). The findings also indicate that the global financial crisis affected both UK Islamic and conventional indices, challenging the notion of the Islamic index as a safe haven. The Shariah screening process does not shield Islamic stock markets from financial downturns. Investors should recognise that the conservative traits of Islamic stocks do not necessarily offer a better investment option, particularly during economic instability.

5.1. Implications

The study provides critical insights for investors on selecting equity indices and commodities to maximise portfolio diversification benefits across different investment horizons. Policymakers should consider these findings for financial stability and investment strategy development. The relative stability of gold during global disruptions suggests its strategic importance in national reserves and financial instruments. Bitcoin's growing prominence but evident volatility calls for regulatory policies that provide clearer guidance while ensuring investor protection. The findings also challenge the notion that Islamic stock indices act as safe havens, highlighting the need to revisit the Shariah screening process.

5.2. Limitations

This study has limitations, including the time frame and dataset size. The results may not fully generalise to other contexts or periods. Additionally, the high volatility of Bitcoin and its evolving market dynamics indicate the need for further research to fully understand its role in diversification.

5.3. Future Research

Future research should employ larger datasets and longer time frames to validate these findings. Alternative methodologies focused on diversification could be explored, particularly in emerging economies like India or Indonesia, to understand how different economic climates affect diversification strategies. Scholars and finance professionals are encouraged to investigate diversification avenues further, considering global financial markets' dynamic and evolving nature.

Funding: This research is supported by the YTI-UKM Distinguished Chair (Grant number: YTI-UKM-2022-004).
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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